autogluon_each_location

October 16, 2023

[6]:
```
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*60*2
presets = 'best_quality'

do_drop_ds = True
# hour, dayofweek, dayofmonth, month, year
use_dt_attrs = ["hour"]
use_estimated_diff_attr = False
use_is_estimated_attr = True

use_groups = False
n_groups = 8

auto_stack = True
num_stack_levels = 2
num_bag_folds = 8


use_tune_data = False
use_test_data = False
tune_and_test_length = 24*30*3 # 3 months from end
holdout_frac = None
use_bag_holdout = False # Enable this if there is a large gap between score_val␣
↪and score_test in stack models.

sample_weight = 'sample_weight' #None
weight_evaluation = True
sample_weight_estimated = 2

run_analysis = True
```

[7]:
```
import pandas as pd
import numpy as np
```

```python
import warnings
warnings.filterwarnings("ignore")


def feature_engineering(X):
    # shift all columns with "1h" in them by 1 hour, so that for index 16:00, we have the values from 17:00
    # but only for the columns with "1h" in the name
    #X_shifted = X.filter(regex="\dh").shift(-1, axis=1)
    #print(f"Number of columns with 1h in name: {X_shifted.columns}")


    columns = ['clear_sky_energy_1h:J', 'diffuse_rad_1h:J', 'direct_rad_1h:J',
       'fresh_snow_12h:cm', 'fresh_snow_1h:cm', 'fresh_snow_24h:cm',
       'fresh_snow_3h:cm', 'fresh_snow_6h:cm']

    X_shifted = X[X.index.minute==0][columns].copy()
    # loop through all rows and check if index + 1 hour is in the index, if so get that value, else nan
    count1 = 0
    count2 = 0
    for i in range(len(X_shifted)):
        if X_shifted.index[i] + pd.Timedelta('1 hour') in X.index:
            count1 += 1
            X_shifted.iloc[i] = X.loc[X_shifted.index[i] + pd.Timedelta('1 hour')][columns]
        else:
            count2 += 1
            X_shifted.iloc[i] = np.nan

    print("COUNT1", count1)
    print("COUNT2", count2)

    X_old_unshifted = X[X.index.minute==0][columns]
    # rename X_old_unshifted columns to have _not_shifted at the end
    X_old_unshifted.columns = [f"{col}_not_shifted" for col in X_old_unshifted.columns]

    # put the shifted columns back into the original dataframe
    #X[columns] = X_shifted[columns]



    date_calc = None
    if "date_calc" in X.columns:
```

```python
        date_calc = X[X.index.minute == 0]['date_calc']

    # resample to hourly
    X = X.resample('H').mean()

    X[columns] = X_shifted[columns]
    #X[X_old_unshifted.columns] = X_old_unshifted

    if date_calc is not None:
        X['date_calc'] = date_calc

    return X




def fix_X(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
 ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)


    X = feature_engineering(X)

    return X



def handle_features(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_X(X_train_observed, "X_train_observed")
    X_train_estimated = fix_X(X_train_estimated, "X_train_estimated")
    X_test = fix_X(X_test, "X_test")


    # add sample weights, which are 1 for observed and 3 for estimated
    X_train_observed["sample_weight"] = 1
    X_train_estimated["sample_weight"] = sample_weight_estimated
    X_test["sample_weight"] = sample_weight_estimated


    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)
```

```python
    return X_train_observed, X_train_estimated, X_test, y_train



def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,␣
 ↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =␣
 ↪handle_features(X_train_observed, X_train_estimated, X_test, y_train)

    if use_estimated_diff_attr:
        X_train_observed["estimated_diff_hours"] = 0
        X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index -␣
 ↪pd.to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
        X_test["estimated_diff_hours"] = (X_test.index - pd.
 ↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

        X_train_estimated["estimated_diff_hours"] =␣
 ↪X_train_estimated["estimated_diff_hours"].astype('int64')
        # the filled once will get dropped later anyways, when we drop y nans
        X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].
 ↪fillna(-50).astype('int64')

    if use_is_estimated_attr:
        X_train_observed["is_estimated"] = 0
        X_train_estimated["is_estimated"] = 1
        X_test["is_estimated"] = 1

    # drop date_calc
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)


    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True,␣
 ↪right_index=True)
```

```python
    # print number of nans in sample_weight
    print(f"Number of nans in sample_weight: {X_train['sample_weight'].isna().sum()}")
    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated, X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
COUNT1 29667
COUNT2 1
COUNT1 4392
COUNT2 2
```

```
COUNT1 702
COUNT2 18
Number of nans in sample_weight: 0
Number of nans in y: 0
Processing location B…
COUNT1 29232
COUNT2 1
COUNT1 4392
COUNT2 2
COUNT1 702
COUNT2 18
Number of nans in sample_weight: 0
Number of nans in y: 4
Processing location C…
COUNT1 29206
COUNT2 1
COUNT1 4392
COUNT2 2
COUNT1 702
COUNT2 18
Number of nans in sample_weight: 0
Number of nans in y: 6059
```

1 Feature enginering

[8]:
```
import numpy as np
import pandas as pd

X_train.dropna(subset=['y'], inplace=True)


for attr in use_dt_attrs:
    X_train[attr] = getattr(X_train.index, attr)
    X_test[attr] = getattr(X_test.index, attr)

print(X_train.head())





if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name␣
 ↪of the column representing locations

    grouped_dfs = []  # To store data frames split by location
```

```
    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()

        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups),␣
 ↪repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())




to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:ms",␣
 ↪"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:cm"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
                     absolute_humidity_2m:gm3  air_density_2m:kgm3  \
ds
2019-06-02 22:00:00                     7.700              1.22825
2019-06-02 23:00:00                     7.700              1.22350
2019-06-03 00:00:00                     7.875              1.21975
2019-06-03 01:00:00                     8.425              1.21800
2019-06-03 02:00:00                     8.950              1.21800

                     ceiling_height_agl:m  clear_sky_energy_1h:J  \
ds
2019-06-02 22:00:00           1728.949951               0.000000
2019-06-02 23:00:00           1689.824951               0.000000
```

```
2019-06-03 00:00:00          1563.224976              0.000000
2019-06-03 01:00:00          1283.425049           6546.899902
2019-06-03 02:00:00          1003.500000         102225.898438

                     clear_sky_rad:W  cloud_base_agl:m  dew_or_rime:idx  \
ds
2019-06-02 22:00:00             0.00       1728.949951              0.0
2019-06-02 23:00:00             0.00       1689.824951              0.0
2019-06-03 00:00:00             0.00       1563.224976              0.0
2019-06-03 01:00:00             0.75       1283.425049              0.0
2019-06-03 02:00:00            23.10       1003.500000              0.0

                     dew_point_2m:K  diffuse_rad:W  diffuse_rad_1h:J  …  \
ds                                                                    …
2019-06-02 22:00:00      280.299988          0.000          0.000000  …
2019-06-02 23:00:00      280.299988          0.000          0.000000  …
2019-06-03 00:00:00      280.649994          0.000          0.000000  …
2019-06-03 01:00:00      281.674988          0.300       7743.299805  …
2019-06-03 02:00:00      282.500000         11.975      60137.601562  …

                     visibility:m  wind_speed_10m:ms  wind_speed_u_10m:ms  \
ds
2019-06-02 22:00:00  40386.476562              3.600               -3.575
2019-06-02 23:00:00  33770.648438              3.350               -3.350
2019-06-03 00:00:00  13595.500000              3.050               -2.950
2019-06-03 01:00:00   2321.850098              2.725               -2.600
2019-06-03 02:00:00  11634.799805              2.550               -2.350

                     wind_speed_v_10m:ms  wind_speed_w_1000hPa:ms  \
ds
2019-06-02 22:00:00               -0.500                      0.0
2019-06-02 23:00:00                0.275                      0.0
2019-06-03 00:00:00                0.750                      0.0
2019-06-03 01:00:00                0.875                      0.0
2019-06-03 02:00:00                0.925                      0.0

                     sample_weight  is_estimated      y  location  hour
ds
2019-06-02 22:00:00              1             0   0.00         A    22
2019-06-02 23:00:00              1             0   0.00         A    23
2019-06-03 00:00:00              1             0   0.00         A     0
2019-06-03 01:00:00              1             0   0.00         A     1
2019-06-03 02:00:00              1             0  19.36         A     2

[5 rows x 50 columns]
```

[9]:
```python
from autogluon.tabular import TabularDataset, TabularPredictor
from autogluon.timeseries import TimeSeriesDataFrame
import numpy as np
train_data = TabularDataset('X_train_raw.csv')
# set group column of train_data be increasing from 0 to 7 based on time, the␣
↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
train_data['ds'] = pd.to_datetime(train_data['ds'])
train_data = train_data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
split_time = pd.to_datetime(train_data["ds"]).max() - pd.
↪Timedelta(hours=tune_and_test_length)
train_set = TabularDataset(train_data[train_data["ds"] < split_time])
test_set = TabularDataset(train_data[train_data["ds"] >= split_time])
if use_groups:
    test_set = test_set.drop(columns=['group'])

if do_drop_ds:
    train_set = train_set.drop(columns=['ds'])
    test_set = test_set.drop(columns=['ds'])
    train_data = train_data.drop(columns=['ds'])


def normalize_sample_weights_per_location(df):
    for loc in locations:
        loc_df = df[df["location"] == loc]
        loc_df["sample_weight"] = loc_df["sample_weight"] /␣
↪loc_df["sample_weight"].sum() * loc_df.shape[0]
        df[df["location"] == loc] = loc_df
    return df

tuning_data = None
if use_tune_data:
    train_data = train_set
    if use_test_data:
        # split test_set in half, use first half for tuning
        tuning_data, test_data = [], []
        for loc in locations:
            loc_test_set = test_set[test_set["location"] == loc]
            loc_tuning_data = loc_test_set.iloc[:len(loc_test_set)//2]
            loc_test_data = loc_test_set.iloc[len(loc_test_set)//2:]
```

```
            tuning_data.append(loc_tuning_data)
            test_data.append(loc_test_data)
        tuning_data = pd.concat(tuning_data)
        test_data = pd.concat(test_data)
        print("Shapes of tuning and test", tuning_data.shape[0], test_data.
 ↪shape[0], tuning_data.shape[0] + test_data.shape[0])

    else:
        tuning_data = test_set
        print("Shape of tuning", tuning_data.shape[0])

    # ensure sample weights for your tuning data sum to the number of rows in␣
 ↪the tuning data.
    tuning_data = normalize_sample_weights_per_location(tuning_data)


else:
    if use_test_data:
        train_data = train_set
        test_data = test_set
        print("Shape of test", test_data.shape[0])

# ensure sample weights for your training (or tuning) data sum to the number of␣
 ↪rows in the training (or tuning) data.
train_data = normalize_sample_weights_per_location(train_data)
if use_test_data:
    test_data = normalize_sample_weights_per_location(test_data)
```

[10]:
```
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_set, label="y",␣
 ↪sample=None)
```

train_data dataset summary

```
                             count  unique top   freq            mean  \
absolute_humidity_2m:gm3     92951     760                   6.017393
air_density_2m:kgm3          92951    1374                   1.255435
ceiling_height_agl:m         76534   63118                 2888.30088
clear_sky_energy_1h:J        92945   48602              515183.641476
clear_sky_rad:W              92951   20312                 143.098015
cloud_base_agl:m             86213   63893                1735.995178
dew_point_2m:K               92951    2006                 275.237958
diffuse_rad:W                92951   11222                  39.395201
diffuse_rad_1h:J             92945   48552              142196.335278
direct_rad:W                 92951   14417                   50.24518
direct_rad_1h:J              92945   41885              180744.819009
effective_cloud_cover:p      92951    5713                   67.08644
```

```
elevation:m                     92951      3                11.401739
fresh_snow_1h:cm                92945     39                 0.009641
fresh_snow_3h:cm                92945     70                 0.029042
fresh_snow_6h:cm                92945     96                 0.058143
hour                            93023     24                11.501338
is_day:idx                      92951      5                 0.483303
is_estimated                    93023      2                 0.118218
is_in_shadow:idx                92951      5                 0.564284
location                        93023      3   A  34085
msl_pressure:hPa                92951   3733              1009.502496
precip_5min:mm                  92951    271                 0.005657
precip_type_5min:idx            92951     15                 0.084348
pressure_100m:hPa               92951   3760               995.818828
pressure_50m:hPa                92951   3809              1001.949597
rain_water:kgm2                 92951     39                 0.009566
relative_humidity_1000hPa:p     92951   3837                73.670589
sample_weight                   93023      6                      1.0
sfc_pressure:hPa                92951   3817              1008.107684
snow_depth:cm                   92951    491                 0.193164
snow_melt_10min:mm              92951     66                 0.000273
snow_water:kgm2                 92951    162                 0.090299
sun_azimuth:d                   92951  88092               179.648569
sun_elevation:d                 92951  76035                -1.206875
super_cooled_liquid_water:kgm2  92951     53                 0.056897
t_1000hPa:K                     92951   1994               279.430664
total_cloud_cover:p             92951   5608                73.692549
visibility:m                    92951  91240              33025.01299
wind_speed_10m:ms               92951    596                 3.038167
wind_speed_u_10m:ms             92951    999                 0.664565
wind_speed_v_10m:ms             92951    850                 0.685095
y                               93023  12379               287.022737

                                          std       min         25%  \
absolute_humidity_2m:gm3             2.711862       0.5       4.025
air_density_2m:kgm3                  0.036567   1.13925     1.23025
ceiling_height_agl:m               2536.68272      27.8  1087.60625
clear_sky_energy_1h:J           820542.211615       0.0         0.0
clear_sky_rad:W                    227.959967       0.0         0.0
cloud_base_agl:m                  1809.297261      27.5     591.925
dew_point_2m:K                       6.829573   247.425      270.75
diffuse_rad:W                       60.518576       0.0         0.0
diffuse_rad_1h:J                 215920.02629       0.0         0.0
direct_rad:W                        112.91716       0.0         0.0
direct_rad_1h:J                 401738.480227       0.0         0.0
effective_cloud_cover:p             34.269564       0.0        42.0
elevation:m                          7.877236       6.0         6.0
fresh_snow_1h:cm                     0.112651       0.0         0.0
fresh_snow_3h:cm                     0.280779       0.0         0.0
```

fresh_snow_6h:cm	0.481544	0.0	0.0
hour	6.920154	0.0	6.0
is_day:idx	0.485974	0.0	0.0
is_estimated	0.322868	0.0	0.0
is_in_shadow:idx	0.483166	0.0	0.0
location			
msl_pressure:hPa	13.085625	944.375	1001.4
precip_5min:mm	0.029169	0.0	0.0
precip_type_5min:idx	0.330071	0.0	0.0
pressure_100m:hPa	13.004987	929.975	987.775
pressure_50m:hPa	13.063835	935.75	993.85
rain_water:kgm2	0.041121	0.0	0.0
relative_humidity_1000hPa:p	14.229107	19.575	64.2
sample_weight	0.288512	0.885256	0.885256
sfc_pressure:hPa	13.124815	941.55	999.975
snow_depth:cm	1.253925	0.0	0.0
snow_melt_10min:mm	0.004249	0.0	0.0
snow_water:kgm2	0.237841	0.0	0.0
sun_azimuth:d	97.282534	6.983	94.67875
sun_elevation:d	23.970707	-49.932	-18.59975
super_cooled_liquid_water:kgm2	0.105794	0.0	0.0
t_1000hPa:K	6.515625	258.025	274.9
total_cloud_cover:p	34.021943	0.0	53.225
visibility:m	17913.98226	132.375	16862.7995
wind_speed_10m:ms	1.760291	0.025	1.675
wind_speed_u_10m:ms	2.802007	-7.225	-1.35
wind_speed_v_10m:ms	1.878808	-8.4	-0.575
y	766.411327	-0.0	0.0

	50%	75%	max	dtypes \
absolute_humidity_2m:gm3	5.45	7.825	17.35	float64
air_density_2m:kgm3	1.255	1.2785	1.441	float64
ceiling_height_agl:m	1887.8875	3988.4125	12294.901	float64
clear_sky_energy_1h:J	4551.0	778482.3	3006697.2	float64
clear_sky_rad:W	1.65	216.8	835.65	float64
cloud_base_agl:m	1164.525	2079.25	11673.725	float64
dew_point_2m:K	274.975	280.5	293.625	float64
diffuse_rad:W	0.925	65.275	334.75	float64
diffuse_rad_1h:J	9952.6	236534.8	1182265.4	float64
direct_rad:W	0.0	29.3	683.4	float64
direct_rad_1h:J	0.0	113395.3	2445897.0	float64
effective_cloud_cover:p	79.95	98.637497	100.0	float64
elevation:m	7.0	24.0	24.0	float64
fresh_snow_1h:cm	0.0	0.0	7.1	float64
fresh_snow_3h:cm	0.0	0.0	20.6	float64
fresh_snow_6h:cm	0.0	0.0	34.0	float64
hour	12.0	17.0	23.0	int64
is_day:idx	0.25	1.0	1.0	float64

is_estimated	0.0	0.0	1.0	int64
is_in_shadow:idx	1.0	1.0	1.0	float64
location				object
msl_pressure:hPa	1010.35	1018.55	1044.1	float64
precip_5min:mm	0.0	0.0	0.6225	float64
precip_type_5min:idx	0.0	0.0	5.0	float64
pressure_100m:hPa	996.75	1004.925	1030.875	float64
pressure_50m:hPa	1002.85	1011.05	1037.25	float64
rain_water:kgm2	0.0	0.0	1.1	float64
relative_humidity_1000hPa:p	76.0	85.05	100.0	float64
sample_weight	0.89831	0.900598	1.801196	float64
sfc_pressure:hPa	1009.0	1017.2	1043.725	float64
snow_depth:cm	0.0	0.0	18.2	float64
snow_melt_10min:mm	0.0	0.0	0.18	float64
snow_water:kgm2	0.0	0.1	5.65	float64
sun_azimuth:d	179.97975	264.41998	348.48752	float64
sun_elevation:d	-0.8645	15.25075	49.94375	float64
super_cooled_liquid_water:kgm2	0.0	0.1	1.375	float64
t_1000hPa:K	278.65002	283.95	303.25	float64
total_cloud_cover:p	93.05	99.9	100.0	float64
visibility:m	36846.176	48308.9875	75489.33	float64
wind_speed_10m:ms	2.7	4.05	13.275	float64
wind_speed_u_10m:ms	0.3	2.5	11.2	float64
wind_speed_v_10m:ms	0.725	1.875	8.825	float64
y	0.0	172.92	5733.42	float64

	missing_count	missing_ratio	raw_type \
absolute_humidity_2m:gm3	72	0.000774	float
air_density_2m:kgm3	72	0.000774	float
ceiling_height_agl:m	16489	0.177257	float
clear_sky_energy_1h:J	78	0.000839	float
clear_sky_rad:W	72	0.000774	float
cloud_base_agl:m	6810	0.073208	float
dew_point_2m:K	72	0.000774	float
diffuse_rad:W	72	0.000774	float
diffuse_rad_1h:J	78	0.000839	float
direct_rad:W	72	0.000774	float
direct_rad_1h:J	78	0.000839	float
effective_cloud_cover:p	72	0.000774	float
elevation:m	72	0.000774	float
fresh_snow_1h:cm	78	0.000839	float
fresh_snow_3h:cm	78	0.000839	float
fresh_snow_6h:cm	78	0.000839	float
hour			int
is_day:idx	72	0.000774	float
is_estimated			int
is_in_shadow:idx	72	0.000774	float
location			object

msl_pressure:hPa	72	0.000774	float
precip_5min:mm	72	0.000774	float
precip_type_5min:idx	72	0.000774	float
pressure_100m:hPa	72	0.000774	float
pressure_50m:hPa	72	0.000774	float
rain_water:kgm2	72	0.000774	float
relative_humidity_1000hPa:p	72	0.000774	float
sample_weight			float
sfc_pressure:hPa	72	0.000774	float
snow_depth:cm	72	0.000774	float
snow_melt_10min:mm	72	0.000774	float
snow_water:kgm2	72	0.000774	float
sun_azimuth:d	72	0.000774	float
sun_elevation:d	72	0.000774	float
super_cooled_liquid_water:kgm2	72	0.000774	float
t_1000hPa:K	72	0.000774	float
total_cloud_cover:p	72	0.000774	float
visibility:m	72	0.000774	float
wind_speed_10m:ms	72	0.000774	float
wind_speed_u_10m:ms	72	0.000774	float
wind_speed_v_10m:ms	72	0.000774	float
y			float

	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	
dew_point_2m:K	numeric	
diffuse_rad:W	numeric	
diffuse_rad_1h:J	numeric	
direct_rad:W	numeric	
direct_rad_1h:J	numeric	
effective_cloud_cover:p	numeric	
elevation:m	category	
fresh_snow_1h:cm	numeric	
fresh_snow_3h:cm	numeric	
fresh_snow_6h:cm	numeric	
hour	numeric	
is_day:idx	category	
is_estimated	category	
is_in_shadow:idx	category	
location	category	
msl_pressure:hPa	numeric	
precip_5min:mm	numeric	
precip_type_5min:idx	category	

pressure_100m:hPa	numeric
pressure_50m:hPa	numeric
rain_water:kgm2	numeric
relative_humidity_1000hPa:p	numeric
sample_weight	category
sfc_pressure:hPa	numeric
snow_depth:cm	numeric
snow_melt_10min:mm	numeric
snow_water:kgm2	numeric
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	numeric
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
y	numeric

test_data dataset summary

	count	unique	top	freq	mean \
absolute_humidity_2m:gm3	5791	289			4.192639
air_density_2m:kgm3	5791	640			1.280018
ceiling_height_agl:m	4395	4247			3278.267059
clear_sky_energy_1h:J	5788	3059			469132.824948
clear_sky_rad:W	5791	2046			130.246477
cloud_base_agl:m	4934	4719			1733.271034
dew_point_2m:K	5791	948			270.733081
diffuse_rad:W	5791	2237			42.175259
diffuse_rad_1h:J	5788	3065			152461.828645
direct_rad:W	5791	1829			51.829421
direct_rad_1h:J	5788	2676			186526.762509
effective_cloud_cover:p	5791	2100			66.598541
elevation:m	5791	3			11.262131
fresh_snow_1h:cm	5788	23			0.032308
fresh_snow_3h:cm	5788	42			0.100259
fresh_snow_6h:cm	5788	60			0.204492
hour	5791	24			11.499396
is_day:idx	5791	5			0.488387
is_estimated	5791	1			1.0
is_in_shadow:idx	5791	5			0.555085
location	5791	3	A	2161	
msl_pressure:hPa	5791	2040			1012.678587
precip_5min:mm	5791	63			0.003687
precip_type_5min:idx	5791	12			0.086039
pressure_100m:hPa	5791	2124			998.781639
pressure_50m:hPa	5791	2134			1005.02648

rain_water:kgm2	5791	7	0.000984
relative_humidity_1000hPa:p	5791	2051	70.810205
sample_weight	5791	1	2.0
sfc_pressure:hPa	5791	2148	1011.29959
snow_depth:cm	5791	78	0.131661
snow_melt_10min:mm	5791	38	0.000695
snow_water:kgm2	5791	68	0.078393
sun_azimuth:d	5791	5681	179.475343
sun_elevation:d	5791	5093	-0.927197
super_cooled_liquid_water:kgm2	5791	31	0.035175
t_1000hPa:K	5791	825	275.185991
total_cloud_cover:p	5791	1838	71.785616
visibility:m	5791	5784	29884.461577
wind_speed_10m:ms	5791	424	3.227599
wind_speed_u_10m:ms	5791	672	0.668019
wind_speed_v_10m:ms	5791	483	0.538344
y	5791	2304	272.991992

	std	min	25%	\
absolute_humidity_2m:gm3	1.300644	1.1	3.35	
air_density_2m:kgm3	0.024372	1.219	1.26375	
ceiling_height_agl:m	2590.751931	27.925	1149.0625	
clear_sky_energy_1h:J	689638.596662	0.0	0.0	
clear_sky_rad:W	191.578221	0.0	0.0	
cloud_base_agl:m	1987.046511	27.5	525.4375	
dew_point_2m:K	4.634046	255.05	268.33749	
diffuse_rad:W	59.158733	0.0	0.0	
diffuse_rad_1h:J	211011.771342	0.0	0.0	
direct_rad:W	110.450287	0.0	0.0	
direct_rad_1h:J	393513.65175	0.0	0.0	
effective_cloud_cover:p	37.583548	0.0	33.6375	
elevation:m	7.8114	6.0	6.0	
fresh_snow_1h:cm	0.170919	0.0	0.0	
fresh_snow_3h:cm	0.425766	0.0	0.0	
fresh_snow_6h:cm	0.738932	0.0	0.0	
hour	6.920293	0.0	6.0	
is_day:idx	0.486436	0.0	0.0	
is_estimated	0.0	1.0	1.0	
is_in_shadow:idx	0.483636	0.0	0.0	
location				
msl_pressure:hPa	13.953847	975.3	1003.875	
precip_5min:mm	0.017701	0.0	0.0	
precip_type_5min:idx	0.393918	0.0	0.0	
pressure_100m:hPa	13.825369	962.4	989.9	
pressure_50m:hPa	13.873049	968.45	996.087475	
rain_water:kgm2	0.009596	0.0	0.0	
relative_humidity_1000hPa:p	14.940249	21.325	60.75	
sample_weight	0.0	2.0	2.0	

```
sfc_pressure:hPa                 13.921629    974.55     1002.25
snow_depth:cm                     0.635847       0.0         0.0
snow_melt_10min:mm                0.007333       0.0         0.0
snow_water:kgm2                   0.189057       0.0         0.0
sun_azimuth:d                    96.891969    14.913   94.264625
sun_elevation:d                  20.775858 -44.28175  -17.109625
super_cooled_liquid_water:kgm2    0.084895       0.0         0.0
t_1000hPa:K                       3.823552   261.975       272.8
total_cloud_cover:p              37.578218       0.0        41.8
visibility:m                  14669.627165    1215.4    18727.05
wind_speed_10m:ms                 1.869023      0.05       1.725
wind_speed_u_10m:ms                3.12501     -7.15       -1.75
wind_speed_v_10m:ms               1.838513      -5.3        -0.8
y                               770.841016      -0.0         0.0

                                    50%          75%         max  dtypes  \
absolute_humidity_2m:gm3            4.3         5.05         7.7  float64
air_density_2m:kgm3               1.279      1.29375     1.37175  float64
ceiling_height_agl:m            2618.95     4661.025   12294.901  float64
clear_sky_energy_1h:J           11008.5     791394.0   2554290.5  float64
clear_sky_rad:W                   2.675      221.925       710.5  float64
cloud_base_agl:m                904.825  2014.962525     10674.3  float64
dew_point_2m:K                    271.6        273.9       280.4  float64
diffuse_rad:W                     1.775      78.4875      311.95  float64
diffuse_rad_1h:J                18860.9   279202.425   1071799.5  float64
direct_rad:W                        0.0      34.0875      530.15  float64
direct_rad_1h:J                     0.0     129529.5   1895533.0  float64
effective_cloud_cover:p          85.375       99.975       100.0  float64
elevation:m                         7.0         24.0        24.0  float64
fresh_snow_1h:cm                    0.0          0.0         2.6  float64
fresh_snow_3h:cm                    0.0          0.0         5.2  float64
fresh_snow_6h:cm                    0.0          0.0         7.5  float64
hour                               11.0         17.0        23.0    int64
is_day:idx                         0.25          1.0         1.0  float64
is_estimated                        1.0          1.0         1.0    int64
is_in_shadow:idx                    1.0          1.0         1.0  float64
location                                                           object
msl_pressure:hPa               1011.625    1023.8125   1041.3501  float64
precip_5min:mm                      0.0          0.0      0.2475  float64
precip_type_5min:idx                0.0          0.0         3.0  float64
pressure_100m:hPa                 997.9     1009.875     1028.05  float64
pressure_50m:hPa                 1004.1    1016.1625     1034.45  float64
rain_water:kgm2                     0.0          0.0       0.175  float64
relative_humidity_1000hPa:p        73.1       82.075        98.0  float64
sample_weight                       2.0          2.0         2.0    int64
sfc_pressure:hPa                1010.35    1022.5125   1040.8501  float64
snow_depth:cm                       0.0          0.0         4.9  float64
snow_melt_10min:mm                  0.0          0.0        0.14  float64
```

snow_water:kgm2	0.0	0.1	2.15	float64
sun_azimuth:d	179.52899	263.49875	347.37848	float64
sun_elevation:d	-0.79825	15.30325	41.13025	float64
super_cooled_liquid_water:kgm2	0.0	0.0	0.75	float64
t_1000hPa:K	275.175	277.525	285.1	float64
total_cloud_cover:p	96.65	100.0	100.0	float64
visibility:m	31311.025	40438.6635	66178.45	float64
wind_speed_10m:ms	2.9	4.45	10.2	float64
wind_speed_u_10m:ms	0.3	2.9	9.95	float64
wind_speed_v_10m:ms	0.625	1.825	7.15	float64
y	0.0	142.906699	5172.64	float64

	missing_count	missing_ratio	raw_type	\
absolute_humidity_2m:gm3			float	
air_density_2m:kgm3			float	
ceiling_height_agl:m	1396	0.241064	float	
clear_sky_energy_1h:J	3	0.000518	float	
clear_sky_rad:W			float	
cloud_base_agl:m	857	0.147988	float	
dew_point_2m:K			float	
diffuse_rad:W			float	
diffuse_rad_1h:J	3	0.000518	float	
direct_rad:W			float	
direct_rad_1h:J	3	0.000518	float	
effective_cloud_cover:p			float	
elevation:m			float	
fresh_snow_1h:cm	3	0.000518	float	
fresh_snow_3h:cm	3	0.000518	float	
fresh_snow_6h:cm	3	0.000518	float	
hour			int	
is_day:idx			float	
is_estimated			int	
is_in_shadow:idx			float	
location			object	
msl_pressure:hPa			float	
precip_5min:mm			float	
precip_type_5min:idx			float	
pressure_100m:hPa			float	
pressure_50m:hPa			float	
rain_water:kgm2			float	
relative_humidity_1000hPa:p			float	
sample_weight			int	
sfc_pressure:hPa			float	
snow_depth:cm			float	
snow_melt_10min:mm			float	
snow_water:kgm2			float	
sun_azimuth:d			float	
sun_elevation:d			float	

super_cooled_liquid_water:kgm2	float
t_1000hPa:K	float
total_cloud_cover:p	float
visibility:m	float
wind_speed_10m:ms	float
wind_speed_u_10m:ms	float
wind_speed_v_10m:ms	float
y	float

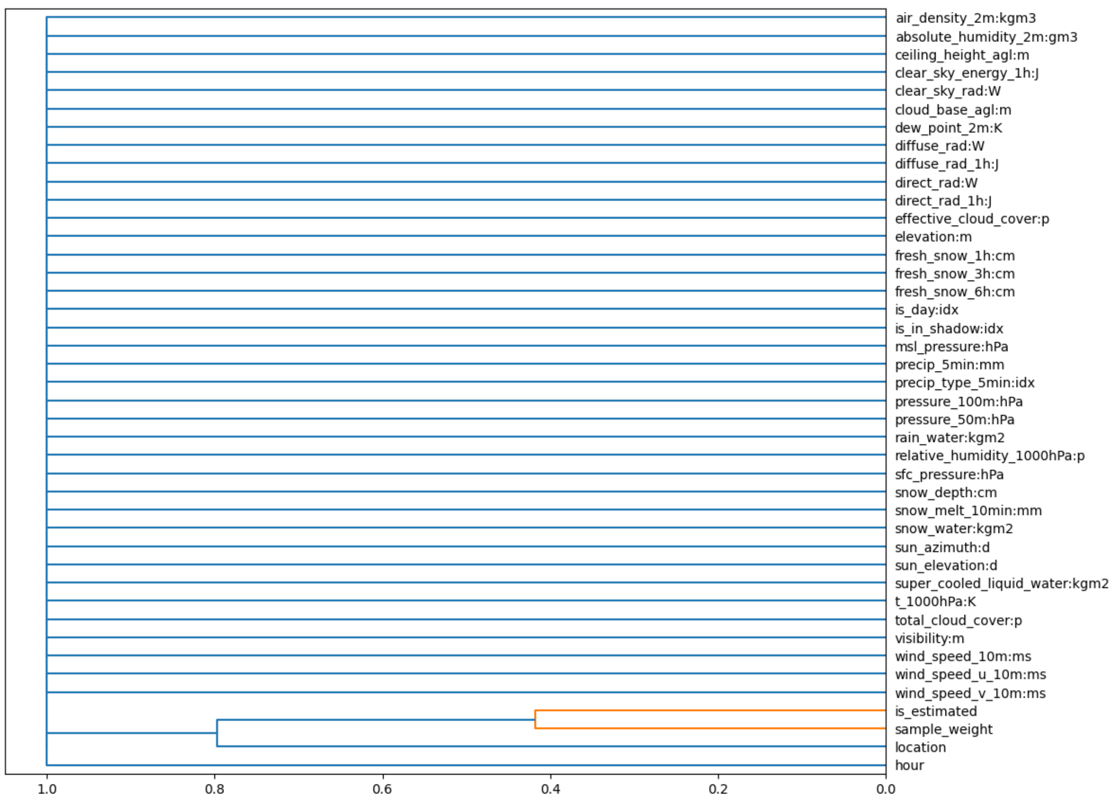
	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	
dew_point_2m:K	numeric	
diffuse_rad:W	numeric	
diffuse_rad_1h:J	numeric	
direct_rad:W	numeric	
direct_rad_1h:J	numeric	
effective_cloud_cover:p	numeric	
elevation:m	category	
fresh_snow_1h:cm	numeric	
fresh_snow_3h:cm	numeric	
fresh_snow_6h:cm	numeric	
hour	numeric	
is_day:idx	category	
is_estimated	category	
is_in_shadow:idx	category	
location	category	
msl_pressure:hPa	numeric	
precip_5min:mm	numeric	
precip_type_5min:idx	category	
pressure_100m:hPa	numeric	
pressure_50m:hPa	numeric	
rain_water:kgm2	category	
relative_humidity_1000hPa:p	numeric	
sample_weight	category	
sfc_pressure:hPa	numeric	
snow_depth:cm	numeric	
snow_melt_10min:mm	numeric	
snow_water:kgm2	numeric	
sun_azimuth:d	numeric	
sun_elevation:d	numeric	
super_cooled_liquid_water:kgm2	numeric	
t_1000hPa:K	numeric	
total_cloud_cover:p	numeric	

```
visibility:m                          numeric
wind_speed_10m:ms                     numeric
wind_speed_u_10m:ms                   numeric
wind_speed_v_10m:ms                   numeric
y                                     numeric
```

Types warnings summary

```
              train_data test_data warnings
sample_weight      float       int  warning
```

1.0.1 Feature Distance

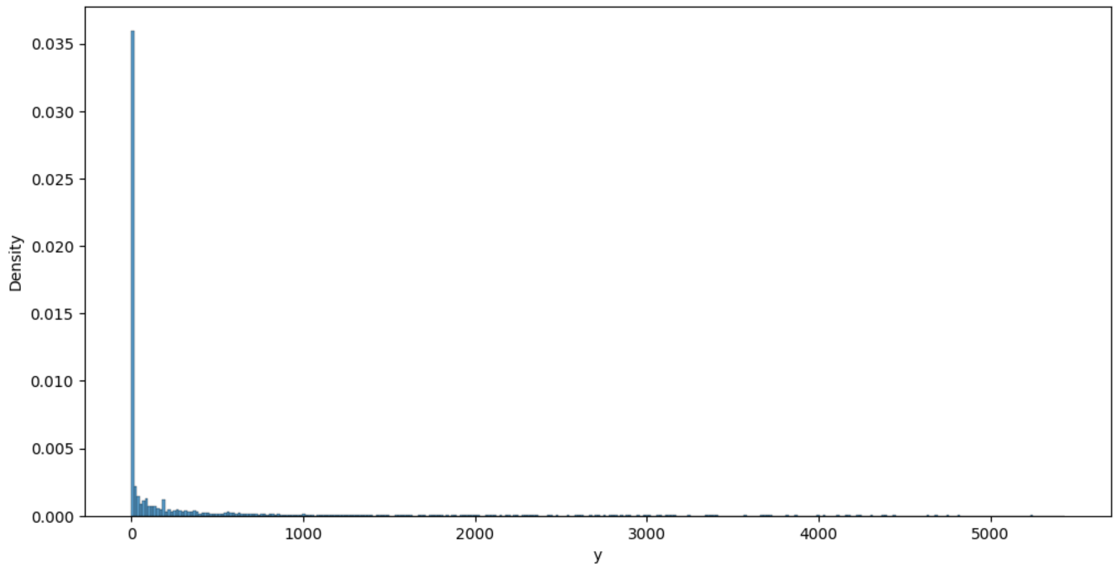



```
[11]: if run_analysis:
          auto.target_analysis(train_data=train_data, label="y")
```

1.1 Target variable analysis

```
   count       mean         std  min  25%  50%    75%      max   dtypes  \
y  10000  283.88153  748.627904  0.0  0.0  0.0  176.4  5428.72  float64

   unique missing_count missing_ratio raw_type special_types
y    2537                                float
```

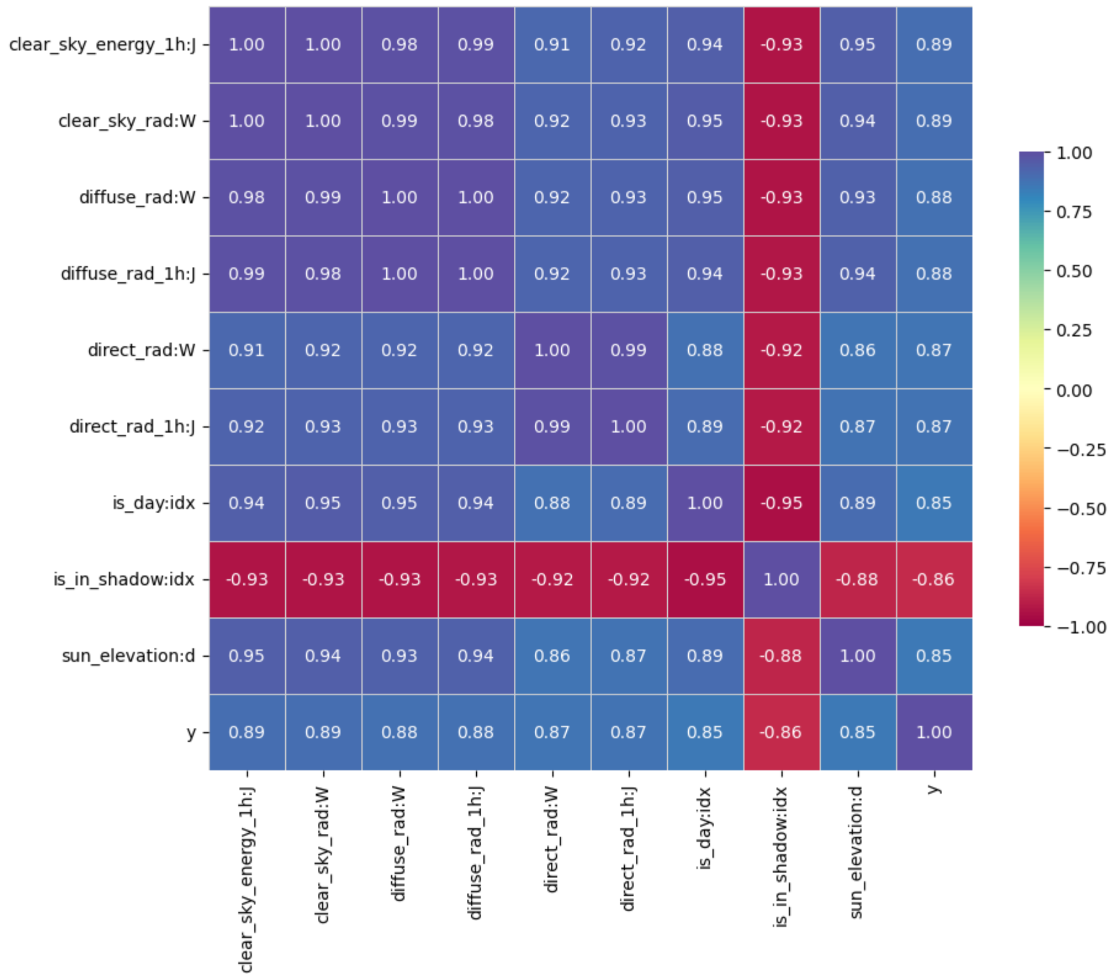


1.1.1 Distribution fits for target variable

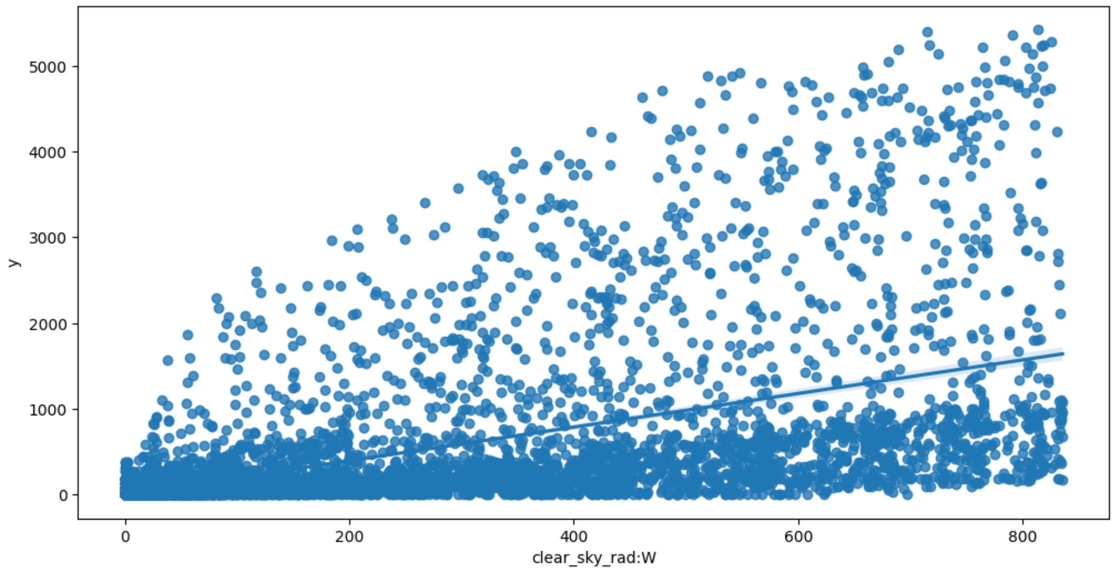
- none of the attempted distribution fits satisfy specified minimum p-value threshold: `0.01`

1.1.2 Target variable correlations

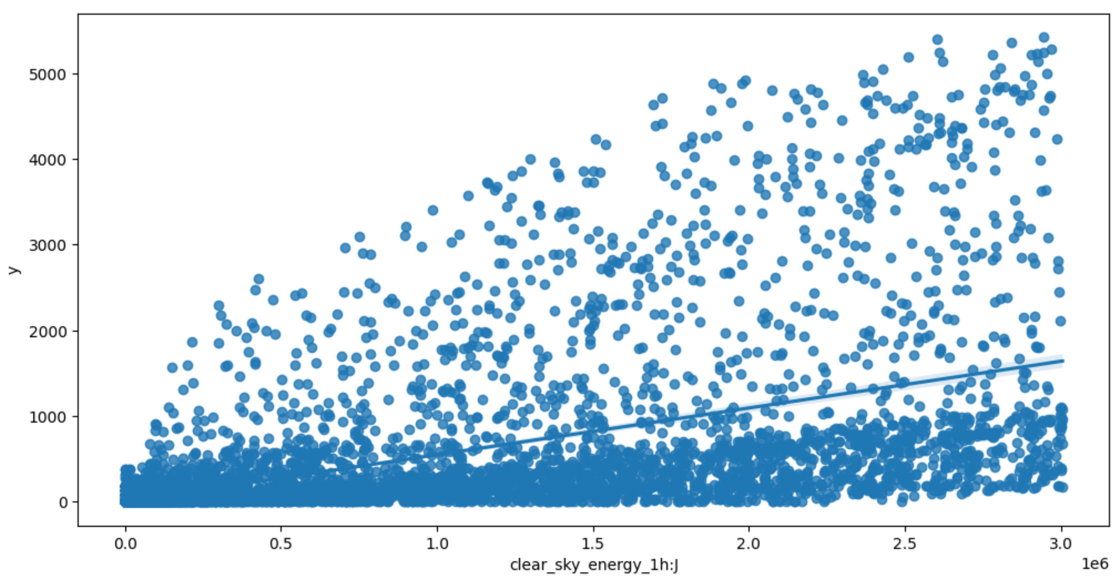
`train_data` - `spearman` correlation matrix; focus: absolute correlation for `y` >= `0.5` (sample size: 10000)



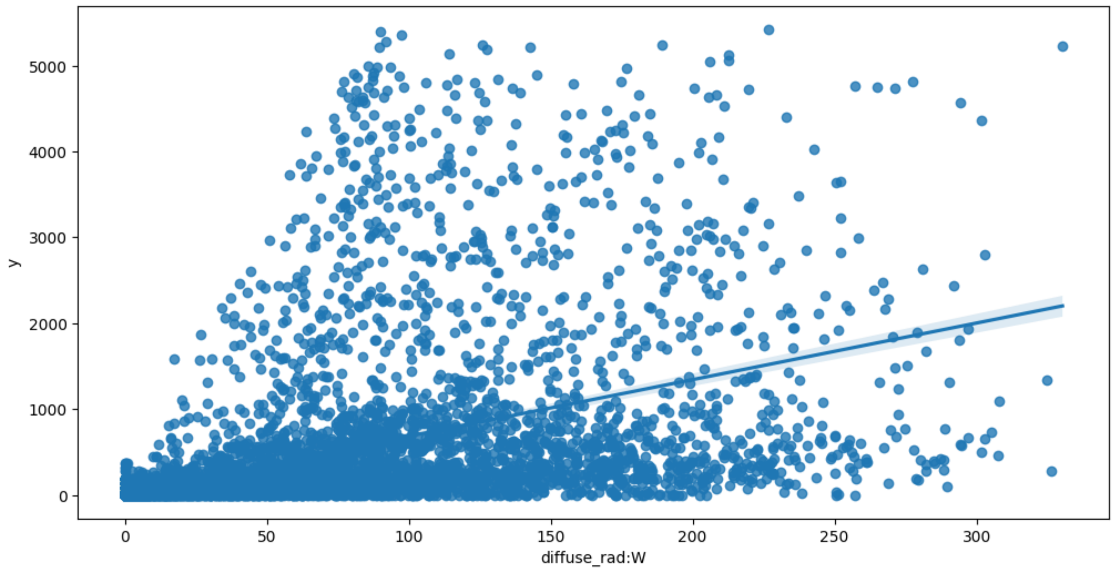
Feature interaction between `clear_sky_rad:W/y` in `train_data` (sample size: 10000)



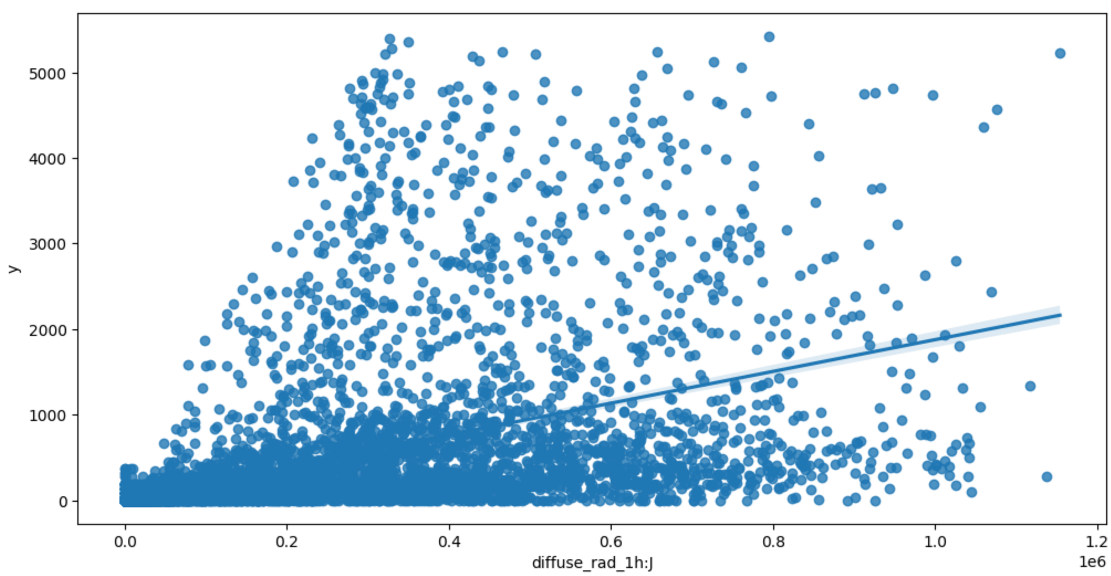
Feature interaction between `clear_sky_energy_1h:J/y` in `train_data` (sample size: 10000)



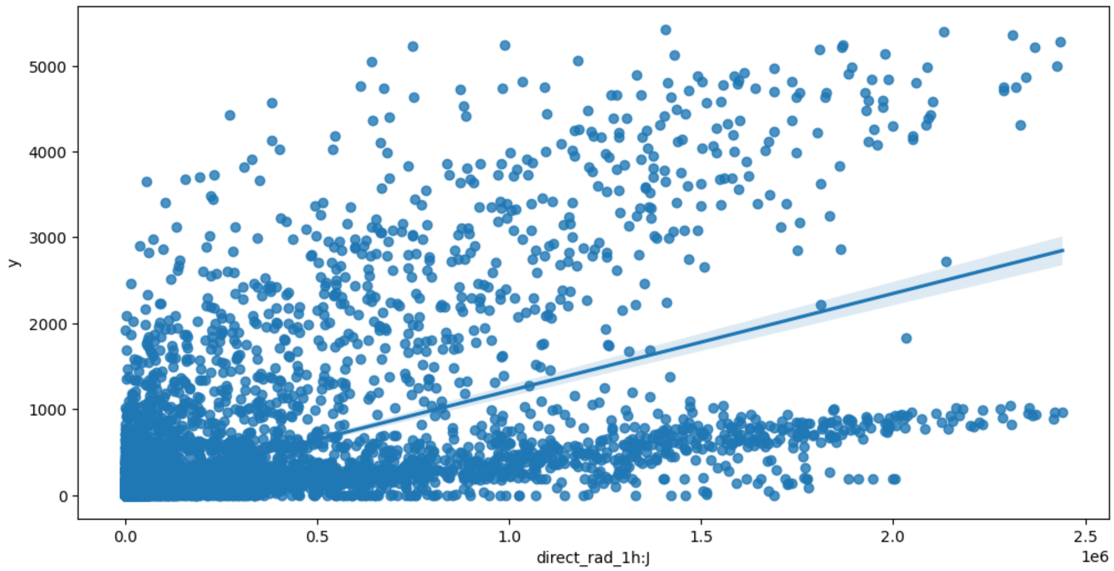
Feature interaction between `diffuse_rad:W/y` in `train_data` (sample size: 10000)



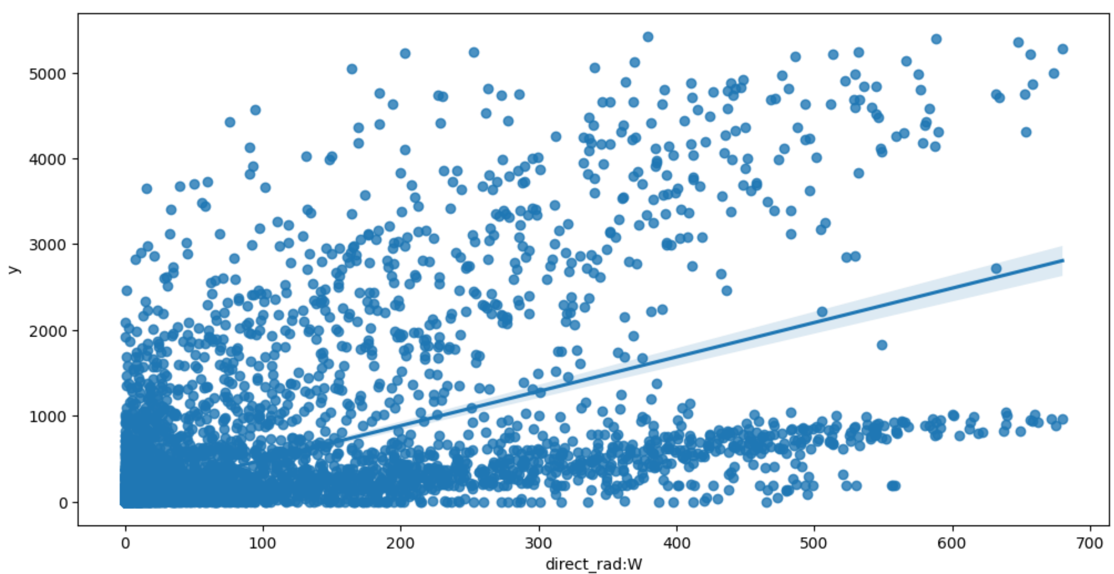
Feature interaction between `diffuse_rad_1h:J`/`y` in `train_data` (sample size: 10000)



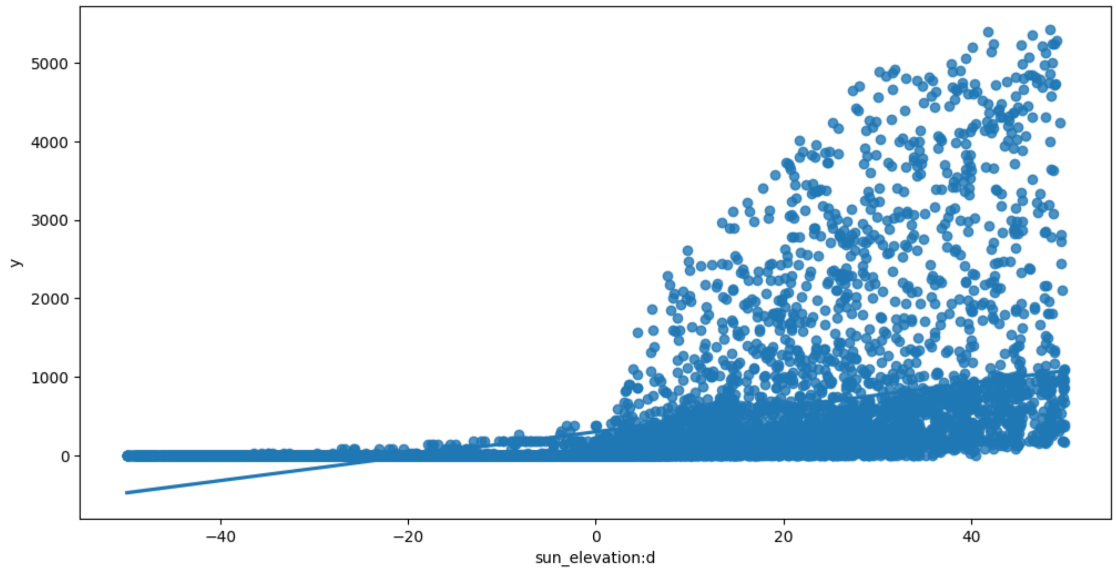
Feature interaction between `direct_rad_1h:J`/`y` in `train_data` (sample size: 10000)



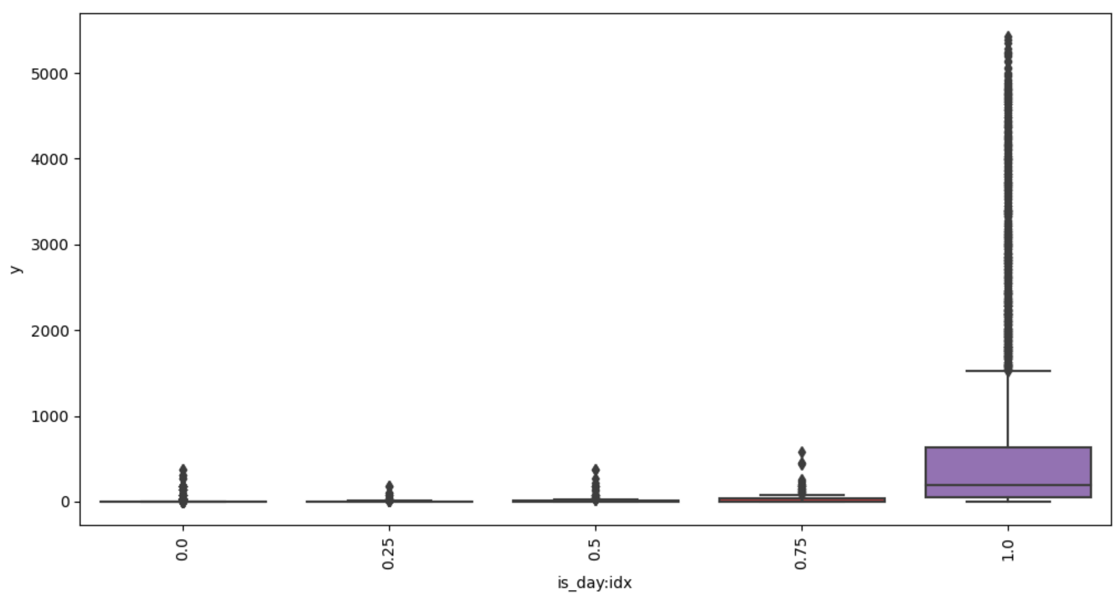
Feature interaction between `direct_rad:W`/y in `train_data` (sample size: 10000)



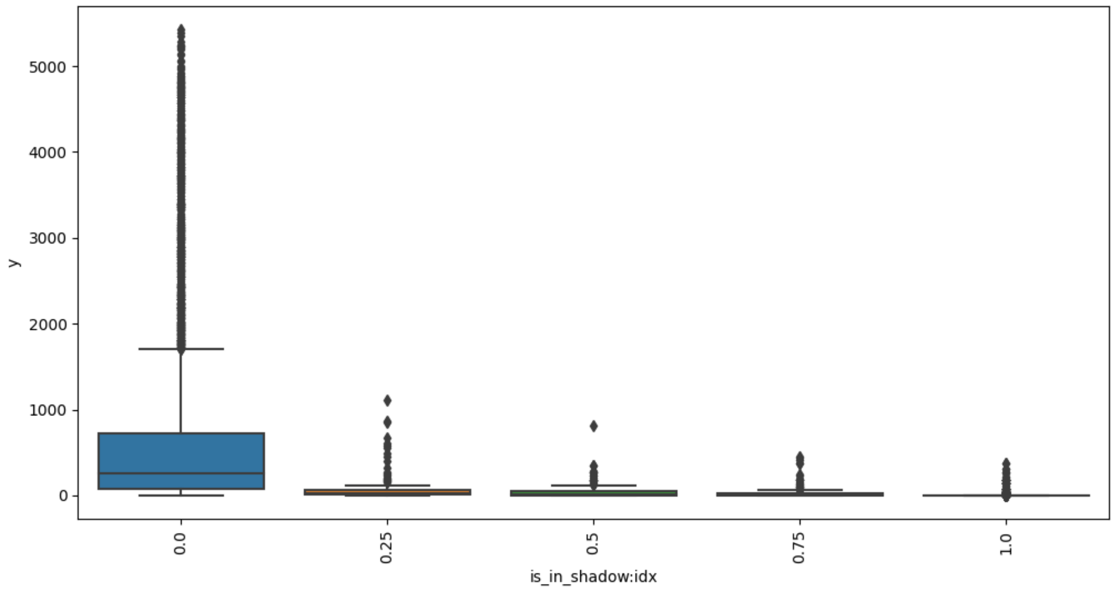
Feature interaction between `sun_elevation:d`/y in `train_data` (sample size: 10000)



Feature interaction between `is_day:idx`/y in `train_data` (sample size: 10000)



Feature interaction between `is_in_shadow:idx`/y in `train_data` (sample size: 10000)



2 Starting

[12]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
 ↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 90
Now creating submission number: 91
New filename: submission_91
```

[13]:
```
predictors = [None, None, None]
```

[ ]:
```python
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both train and tune data and test data
    print("Train data sample weight sum:", train_data[train_data["location"] == loc]["sample_weight"].sum())
    print("Train data number of rows:", train_data[train_data["location"] == loc].shape[0])
    if use_tune_data:
        print("Tune data sample weight sum:", tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
        print("Tune data number of rows:", tuning_data[tuning_data["location"] == loc].shape[0])
    if use_test_data:
        print("Test data sample weight sum:", test_data[test_data["location"] == loc]["sample_weight"].sum())
        print("Test data number of rows:", test_data[test_data["location"] == loc].shape[0])
    predictor = TabularPredictor(
        label=label,
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        sample_weight=sample_weight,
        weight_evaluation=weight_evaluation,
        groups="group" if use_groups else None,
    ).fit(
        train_data=train_data[train_data["location"] == loc],
        time_limit=time_limit,
        presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put somethin, will be overwritten anyways
        tuning_data=tuning_data[tuning_data["location"] == loc] if use_tune_data else None,
        use_bag_holdout=use_bag_holdout,
        holdout_frac=holdout_frac,
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.drop(columns=["sample_weight"])
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])
```

```python
    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=2, num_bag_folds=8,
num_bag_sets=20
Values in column 'sample_weight' used as sample weights instead of predictive
features. Evaluation will report weighted metrics, so ensure same column exists
in test data.
Beginning AutoGluon training … Time limit = 7200s
AutoGluon will save models to "AutogluonModels/submission_91_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   292.91 GB / 315.93 GB (92.7%)
Train Data Rows:    34085
Train Data Columns: 42
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 630.59471,
1165.90242)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    132175.85 MB
        Train Data (Original)  Memory Usage: 12.88 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
```

```
Training model for location A…
Train data sample weight sum: 34084.999999999985
Train data number of rows: 34085
	Stage 5 Generators:
		Fitting DropDuplicatesFeatureGenerator…
	Useless Original Features (Count: 1): ['location']
		These features carry no predictive signal and should be manually
investigated.
		This is typically a feature which has the same value for all
rows.
		These features do not need to be present at inference time.
	Types of features in original data (raw dtype, special dtypes):
		('float', []) : 38 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
		('int', [])   :  2 | ['is_estimated', 'hour']
	Types of features in processed data (raw dtype, special dtypes):
		('float', [])     : 37 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
		('int', [])       :  1 | ['hour']
		('int', ['bool']) :  2 | ['elevation:m', 'is_estimated']
	0.1s = Fit runtime
	40 features in original data used to generate 40 features in processed
data.
	Train Data (Processed) Memory Usage: 10.43 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.18s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
	This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
	To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
	'NN_TORCH': {},
	'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
	'CAT': {},
	'XGB': {},
	'FASTAI': {},
	'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
	'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
```

```
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 3 stack levels (L1 to L3) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 3199.12s of
the 7199.82s of remaining time.
        -216.24  = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.4s     = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 3198.57s of
the 7199.27s of remaining time.
        -217.2002        = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.41s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 3198.07s of the
7198.77s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -144.3217        = Validation score   (-mean_absolute_error)
        39.27s   = Training   runtime
        19.74s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 3149.64s of the
7150.33s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -154.9519        = Validation score   (-mean_absolute_error)
        45.99s   = Training   runtime
        19.51s   = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 3100.25s of
the 7100.95s of remaining time.
        -168.8812        = Validation score   (-mean_absolute_error)
        10.78s   = Training   runtime
        1.43s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 3087.38s of the
7088.08s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -161.7348        = Validation score   (-mean_absolute_error)
        210.57s  = Training   runtime
        0.13s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 2875.79s of the
6876.48s of remaining time.
        -169.8924        = Validation score   (-mean_absolute_error)
        2.16s    = Training   runtime
```

```
        1.43s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 2871.53s of
the 6872.23s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -173.9881        = Validation score   (-mean_absolute_error)
        41.79s   = Training   runtime
        0.65s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 2828.62s of the
6829.32s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -164.8785        = Validation score   (-mean_absolute_error)
        64.66s   = Training   runtime
        4.85s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 2760.45s of
the 6761.14s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -160.3243        = Validation score   (-mean_absolute_error)
        126.45s  = Training   runtime
        0.37s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 2632.7s of the
6633.4s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -151.5461        = Validation score   (-mean_absolute_error)
        143.83s  = Training   runtime
        23.03s   = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 2483.75s of the
6484.45s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -141.0915        = Validation score   (-mean_absolute_error)
        78.03s   = Training   runtime
        40.83s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 2440.34s of the
6441.03s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -150.7559        = Validation score   (-mean_absolute_error)
        92.34s   = Training   runtime
        36.82s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 2390.73s of the
6391.43s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

```
        -157.998         = Validation score   (-mean_absolute_error)
        420.05s  = Training   runtime
        0.26s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 2180.02s of
the 6180.72s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -170.7462        = Validation score   (-mean_absolute_error)
        84.37s   = Training   runtime
        1.33s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 2136.17s of the
6136.87s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -160.2333        = Validation score   (-mean_absolute_error)
        135.2s   = Training   runtime
        11.0s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 2062.87s of
the 6063.56s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -156.8688        = Validation score   (-mean_absolute_error)
        239.65s  = Training   runtime
        0.76s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1948.46s of the
5949.15s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -149.0872        = Validation score   (-mean_absolute_error)
        287.51s  = Training   runtime
        45.17s   = Validation runtime
Repeating k-fold bagging: 3/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1799.11s of the
5799.8s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.2858        = Validation score   (-mean_absolute_error)
        117.35s  = Training   runtime
        59.43s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1755.46s of the
5756.15s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -149.7701        = Validation score   (-mean_absolute_error)
        139.18s  = Training   runtime
        50.17s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1705.76s of the
5706.46s of remaining time.
```

```
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -156.941         = Validation score   (-mean_absolute_error)
        630.37s  = Training   runtime
        0.4s     = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1494.27s of
the 5494.96s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -169.6431        = Validation score   (-mean_absolute_error)
        126.47s  = Training   runtime
        1.96s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1450.8s of the
5451.5s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -158.8005        = Validation score   (-mean_absolute_error)
        198.17s  = Training   runtime
        12.93s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1385.03s of
the 5385.73s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

[ ]:
```
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
```

[ ]:
```
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
```

3 Submit

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

[ ]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
↪"location"], left_on=["ds", "location"])
```

```
#test_data_merged
```

```
[ ]: # predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
 ↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
    past_pred = predictors[i].
 ↪predict(train_data_with_dates[train_data_with_dates["location"] == loc])
    train_data_with_dates.loc[train_data_with_dates["location"] == loc,␣
 ↪"prediction"] = past_pred
```

```
[ ]: # plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
 ↪y='y', ax=ax, label="train data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
 ↪y='prediction', ax=ax, label="past predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```

```
[ ]: # concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[ ]:
```
# Save the submission DataFrame to submissions folder, create new name based on␣
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),␣
↪index=False)
print("jall1a")
```

[ ]:
```
# save this running notebook
from IPython.display import display, Javascript
import time

# hei123

display(Javascript("IPython.notebook.save_checkpoint();"))

time.sleep(3)
```

[ ]:
```
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

[ ]:
```
# feature importance
location="A"
split_time = pd.Timestamp("2022-10-28 22:00:00")
estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
estimated = estimated[estimated["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=estimated,␣
↪time_limit=60*10)
```

[ ]:
```
# feature importance
observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
observed = observed[observed["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=observed,␣
↪time_limit=60*10)
```

[ ]:
```
display(Javascript("IPython.notebook.save_checkpoint();"))
time.sleep(3)

subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
↪"autogluon_each_location.ipynb"])
```

[ ]:
```
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command,␣
↪stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').
↪strip()}")
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email',␣
↪'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is␣
↪not None else 'Henrik eller Jørgen'])

# branch_name = new_filename

# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push',␣
↪'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
#     execute_git_command(git_repo_path, ['push', '--set-upstream',␣
↪'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```